Participation in Open Knowledge Communities and Career Development: Evidence from Enterprise Software

Peng Huang
Department of Decision, Operations and Information Technologies
R. H. Smith School of Business, University of Maryland
College Park, MD 20742
huang@umd.edu

Zhongju Zhang
Department of Operations and Information Management
School of Business, University of Connecticut
2100 Hillside Road, Storrs, CT 06269
john.zhang@business.uconn.edu

Abstract

Using longitudinal data of IT professionals' activities in the SAP Community Network, and the complete career histories of those professionals, obtained from LinkedIn, we investigate the relationship between participation in Internet-enabled open knowledge communities and a major career event: job hopping. We characterize individual participation in open knowledge communities by three types of related activities: contribution, learning, and the social capital accrued during the interaction with other community members. We find that while contributing behavior leads to a higher likelihood of job hopping, greater amount of learning is associated with a higher probability of staying with the current employer. In addition, we find that the social capital one builds through the interaction with others in the knowledge community moderates these relationships. Our work contributes to the existing literature on communities of practice by demonstrating that participation in these networks indeed lead to realization of career benefits, highlighting the importance of extrinsic motives in encouraging participation. In addition, our study takes the first step to bridge the gap in the current literature on employee turnover that has so far ignored the impacts of employee participation in external knowledge communities, thus providing both theoretical and practical implications in the area of organizational research.

Key words: online forums; community of practice; knowledge management; knowledge community; job hopping; career development; enterprise software

1. Introduction

Over the last decade, many firms have implemented knowledge management systems to actively promote the codification, sharing, and transferring of knowledge within the organization (Alavi and Leidner 2001). While traditional knowledge management systems are usually confined within the boundary of an organization, an emerging organizational form of managing knowledge — Internet-enabled communities of practice [1]— has become increasingly popular and has drawn wide participations from practitioners and innovators (Millen and Fontaine 2003, Wenger and Snyder 2000). A growing body of literature has started to investigate this form of knowledge management practice. For example, recent research has theorized the community-based model of knowledge creation as an evolutionary process of learning driven by criticism (Lee and Cole 2003). Some suggest that communities of practice help to solve problems quickly, facilitate the spreading of best practices by harnessing expertise dispersed among community members, and create high quality and variety of innovations (Füller et al. 2007, Wenger and Snyder 2000). In addition, individual participants of these communities are likely to learn from their peers, develop professional skills, and build social connections (Wasko and Faraj 2005).

Although progress has been made, there remain at least two related issues that challenge the current understanding of Internet-enabled communities of practices. First, similar to open source communities and mass collaboration platforms (Zhang and Wang 2012), the essence of this model of knowledge creation and innovation is based on self-organizing and voluntary contribution, which is inherently informal and lacks tightly-controlled structures. To the extent that contribution to these communities are similar to the creation of public goods (Wasko and Faraj 2000), it is difficult to motivate members to actively participate and contribute to these

[1] According to Wasko and Faraj (2005), a network of practice is a large, loosely knit, geographically distributed group of individuals engaged in a shared practice, which often coordinate through third-parties such as professional associations and exchange knowledge through conferences and publications.

communities. Some research has offered insights on the incentives to contribute to such communities (Ma and Agarwal 2007, Roberts et al. 2006, Wasko and Faraj 2005). In general, they found that participants are usually driven by both intrinsic (such as the sense of fulfillment and satisfaction, expression of creativity, enjoyment) and extrinsic (such as economic incentives or self-interest) motives (Lerner and Tirole 2002, Roberts et al. 2006). However, aside from anecdotal evidences or surveys, large scale empirical studies on the economic benefits of participation are lacking. Second, a particular thorny issue of governing knowledge management practices emerges when employees of an organization participate in a community of practice that spans outside of the boundary of the organization. While participation may bring learning benefits (Brown and Duguid 1991), such activities may also lead to dual allegiance (Chan and Husted 2010, Gordon 1990) that cause tension and possible conflict between the external community and the organization — especially when the individual knowledge sharing behavior deviates from what the organization expects, such as unintended knowledge spillover to people outside the organization, or the exchange of career-related information such as job opportunities. Empirical studies on this subject are scarce, and current research sheds very little insights on how to manage employee's participation activities in external knowledge communities.

In this study we attempt to provide answers to these questions by investigating how participation in an open community of practice related to enterprise software impacts the career development of IT professionals, particularly their job hopping behavior. Job hopping between companies is one of the major events in an employee's career development. In addition, job hopping is likely a facilitator of knowledge spillover, which can impose significant costs on employers (Fallick et al. 2006, Tambe and Hitt 2010). We measure individual participation in open knowledge communities by three types of related activities: contribution, learning, and the accumulation of social capital through interactions with other community members. We find that while contributing behavior leads to a higher likelihood of job hopping, greater amount of learning is associated with a higher probability of staying with the current employer. In addition, we find that the social capital one builds through the interaction with others in the knowledge community moderates these relationships.

2. Theory and Hypotheses

The success of online communities of practice depends on their ability to attract, engage, and motivate members to participate and contribute knowledge that is both relevant and valuable to the community members (Wenger et al. 2002). To explain the voluntary knowledge contribution behavior in these communities, prior research has theorized a number of motivations (Roberts et al. 2006, Rossi 2004). Many argued that intrinsic motivations such as self-needs, enjoyment, personal satisfaction are important factors behind such altruistic behavior (Lakhani and von Hippel 2003, Wasko and Faraj 2005). On the other hand, some researchers proposed that contributors are able to internalize extrinsic motivation, and therefore such contributions may generate tangible benefits in the long term (Roberts et al. 2006). Such extrinsic motivations may include career rewards – i.e. potential future job offers (Lerner and Tirole 2002), enhanced reputation (Lakhani and von Hippel 2003, Wasko and Faraj 2005), and status seeking (Lampel and Bhalla 2007).

We believe that extrinsic motivations such as expected career benefits play a significant role in user participation in open knowledge communities. By actively making contribution in these communities, users have the opportunity to gain visibility and establish themselves as experts in the field of their profession (Ardichvili et al. 2003), which could result in job opportunities when they look for alternative employment or new business ventures (Wilson

2009). Anecdotal evidences also seem to support this proposition. For example, Lerner and Tirole (2002) documented that many developers of an open source Web server software – Apache –have subsequently been hired by companies such as IBM or Collab.Net.

Furthermore, the open competition for other companies' talent – also known as strategic poaching – has become an popular practice in business (Cappelli 2000). Bringing in experienced outside experts not only helps to fill in key positions in an organization, but also imports knowledge that it needs to expand into new market or launch new lines of businesses. Given that active contribution increases an individual's visibility, status and reputation among peers in the same profession within the knowledge community and beyond the boundary of her own organization, people who make knowledge contribution are more likely to appear on the radar of recruiters and competing firms in the industry. Therefore these individuals are provided with greater access to outside career opportunities and are more likely to jump ship.

H1: A higher level of contribution to Internet-based communities of practice is associated with a greater likelihood of job hopping.

While knowledge contributors may gain greater visibility to outside firms and thus are more likely to leave their current employer, some members choose to be primarily knowledge seekers in the community and become the recipients of the knowledge exchanges. These types of users may also derive tangible benefits from their involvement in the community. In contrast to learning through conventional on-job training, learners (or knowledge seekers) in knowledge communities are enculturated and are acquiring not only explicit, formal knowledge but also a community's collective viewpoint, language, and the embodied ability to behave as community members (Brown and Duguid 1991). Even though community members are engaged in learning to achieve their own goals, they typically do so within the context of a firm's objectives, thus benefiting their employers (O'Mahony and Ferraro 2007). Such learning often represents a nontransferable, relationship-specific investment (Joskow 1987, Rylander et al. 1997) on the part of the employee in her organization, and strengthens the employee's organizational commitment (Porter et al. 1974) to her employer, leading to reduced turnover intention. In addition, by proactively learning from communities of practice, individuals can expand their skill set, improve their work productivity and job performance within an organization, and enjoy higher level of job satisfaction, thus are less likely to leave their current employers.

H2: A higher level of learning from Internet-based communities of practice is associated with a lower likelihood of job hopping.

An individual's social capital, accumulated through interactions with other members in the knowledge communities, may also influence one's career development such as job hopping (Adler and Kwon 2002, Seibert et al. 2001). Theoretical development linking social capital with career outcomes has offered several alternative explanations (Burt 1992, 2000, Granovetter 1973). Following prior literature (McPherson et al. 1992), we argue that when an individual joins an open knowledge community outside her organization, she is connected to other community members through her interactions with them. Individuals that occupy structurally advantageous positions in the knowledge community gain unique and timely access to information, have greater bargaining power and therefore control over resources and outcomes, and enjoy greater visibility and career opportunities in the social system *outside* their employer organizations (Seibert et al. 2001). Specifically, an individual with a high social capital within the knowledge community is more embedded with peers in the same profession external to her employer, which may lead to decay of attachment with her own employer (Mossholder et al. 2005). Thus she is more likely to leave for new jobs when the opportunities knock.

H3: A higher level of social capital in Internet-based communities of practice is associated with a greater likelihood of job hopping.

The contingent value of social capital has been emphasized in prior literature (Belliveau et al. 1996, Burt 1997, Podolny and Baron 1997). For example, Burt (1997) argues that the return to human capital, such as intelligence, education, and seniority at least partially depend on a person's structural location within her social network. We argue that social capital and human capital provide alternative ways for accessing external job opportunities. Adler and Kwon (2002) point out that individuals can sometimes compensate for a lack of financial or human capital by superior connections. In other words, as social capital increases, people will leverage more of their social connections rather than their human capitals when searching for jobs because they are better connected. Hence we expect that the marginal effect of knowledge contribution on job hopping is weaker for people with a high level of social capital.

H4: Social capital in Internet-based communities of practice moderates the effect of knowledge contribution on job hopping, such that the positive effect of contribution on job hopping becomes weaker when social capital is high.

The interaction effect of learning and network characteristics has been thus far examined primarily at the firm level. Hagedoorn and Duysters (2002) argued that in a dynamic environment, companies that learn from a variety of sources through the network they are operating will be more effective. Gilsing et al. (2008) demonstrated that the interaction between technological distance (a special case of cognitive distance) and network betweenness centrality has a negative effect on a firm's exploration and innovative performance. Extending this line of research, we argue that the (negative) effect of learning on job hopping becomes greater with an increase in social capital in knowledge communities. When individuals interact with a structurally diverse group of peers, external knowledge learning becomes more valuable because they are exposed to unique sources of knowledge (Cummings 2004), which in turn results in further improved job performance and productivity with the current employer, and greater job satisfaction. These individuals are even less likely to switch jobs.

H5: Social capital in Internet-based communities of practice moderates the effect of learning on job hopping, such that the negative effect of learning on job hopping becomes greater (more negative) when social capital is high.

Our proposed research model is presented in Figure 1.

[Insert Figure 1 Here]

3. Data and Methods

Our research setting is the knowledge community sponsored by SAP AG, the largest enterprise software vendor by revenue. As part of its platform strategy to engage its customers and partners, SAP established Internet-based SAP Community Network (SCN) in 2004. The online community serves as a resource repository and a platform for SAP users, developers, architects, consultants and integrators to collaborate and exchange knowledge on the adoption, implementation, and customization of SAP solutions. As of 2010, the SCN has over 276,000 active registered users from 224 different countries. A unique feature of the SCN is that its members' participation and contribution in the community is tractable. To reward active members, SAP has developed a Contributor Recognition Program (CRP), which awards points to community members for the contribution they make. For example, in the case of forum discussion participation, 2, 6, or 10 points may be awarded for forum posts replying to existing threads marked as questions, depending on the *helpfulness* of the answer.

To track information flows between the members of the SAP Community Network, we focus on user interactions through the most frequently used communication format: the discussion forums. A discussion *thread* is initiated by a knowledge seeker, who posts a specific technical question in a topic forum of her choice. Knowledge contributors, on the other hand, respond to the question and try to solve the problem by posting messages to the discussion thread. The discussion thread is thus comprised of a list of *messages*, and each message (either a question or a subsequent answering attempt) contains the information about the member who posts the message, the body of the message, and a time stamp. Once a correct solution (at the discretion of the knowledge seeker) is received, the discussion thread is closed.

We assembled a dataset of IT professionals who participated in the SAP Community Network during the period of 2004-2011. Our data come from several sources. Specifically, we developed a Web scripting tool and obtained the complete history of SCN forum discussions as well as the user profiles of all registered members from 2004 to 2011. In addition, we used data on LinkedIn, the professional social network website, to obtain the complete career trajectories of the individuals in our sample. We also supplement our individual level data with information on the companies that employ these individuals, using data obtained from the Compustat database, LinkedIn, and the Company Insight Center (CIC) database.

The sample of our analyses is constructed in the following way. From the user profiles that we obtained from the SAP Community Network, we selected the subset of registered users who are located in the United States, and who choose to disclose their company affiliations in their user profiles. This left us with 8,815 individuals with complete records. The next step involved matching the registered members to their professional profiles on LinkedIn to obtain their career histories. To ensure the quality of the matching, we performed a manual search on

LinkedIn website using the first name, last name, and company for each of the 8,815 registered members. We discarded records for those who we cannot find a matching profile on LinkedIn, or those with multiple matching profiles because we cannot uniquely identify the correct person. Finally, we removed temporary contract workers who have obtained a degree outside the US, *and* who have changed job at least five times during a 3-year period. This resulted in a sample of 6,470 individual-year observations for 904 IT professionals over an 8-year sample period.

Dependent Variable

The primary dependent variable in our analyses is the job hopping (or voluntary turnover) behavior of the individuals who participate in the SAP Community Network. To determine if a job hopping occurs for individual *i* at year *t*, we first extract the individual's company affiliation ($Company_{i,t}$) and job title on January 1st at year *t* based on the job histories we obtained from LinkedIn. An indicator variable, Job_Switch_{it}, is then created and is set to 0 if $Company_{i,t}$ and $Company_{i,t+1}$ are identical, and to 1 if $Company_{i,t+1}$ is different from $Company_{i,t}$.

Independent Variables

Contribution. We measure a user's contribution to the knowledge community using forum Q&A discussions that took place in the SAP Community Network. Specifically, the rules of SAP reward program specify that, for each question that is posted in a topic forum, the knowledge seeker may use her discretion to judge the quality of answers posted by knowledge contributors. The knowledge seeker can distribute 10 reward points to a user whose answer is deemed correct (at most 1 answer can be evaluated as correct), 6 points if very helpful (at most 2 answers), and 2 points if helpful (no limit on number of helpful answers). For each individual *i* at year *t*, we retrieve the history of her posts to answer knowledge seekers' questions. Based on the number of her posts evaluated by the knowledge seeker as correct, very helpful, or helpful, we compute the total reward points she earned. We use the number of total reward points that one earned by the end of year t, $Contribution_{i,t}$, as a proxy to measure her cumulative contribution to the community.

Learning. The amount of knowledge that a user learned from her peers in the knowledge community is defined in a similar fashion. For each individual i at year t we retrieve all the discussion threads that were initiated by i prior to the end of year t, and examine the history of the answers posted by other forum members. If i received any correct, very helpful, or helpful answers in year t, the number of reward points she gave to the knowledge contributors in recognition of their help is used as a proxy for inward knowledge flow (learning) to i. Cumulative $Learning_{i,t}$ is defined as the sum of the reward points individual i gave prior to the end of year t across all threads initiated by i.

Social Capital. We use Freeman's (1979) "*betweenness centrality*" as a measure of the extent to which individuals occupy structurally advantageous positions and bridge structure holes in the professional community network. To derive the measurement of betweenness centrality for each individual, we constructed a two-mode, affiliation network where individuals are treated as network nodes and discussion threads are treated as events or ties that link the individuals. It is noted that the resulting network is dynamic and its structures vary from year to year. Therefore variable $betweenness\_centrality_{i,t}$ also changes over time.

Control Variables

We control for a series of variables at both the individual and the firm level. At the individual level, we control for the participants' education background (college, master, and doctoral degree), tenure with the current company, tenure with the current job position, affiliation with SAP, and nature of jobs (management/technical IT professionals, and non-IT function). At the firm level, we control for the employer's industry, the type of the organization, and the size of the firm measured by the number of employees.

The summary statistics of some key variables are presented in Table 1.

[Insert Table 1 Here]

Empirical Models

We chose the Cox proportional hazard model as our model specification. The hazard rate for the ith subject at time t is specified as $h_i(t|\mathbf{x}_{i,t}) = h_0(t)\exp(\mathbf{x}_{i,t}\boldsymbol{\beta})$, where

$$\boldsymbol{x}_{i,t}\boldsymbol{\beta} = \beta_0 Contribution_{i,t} + \beta_1 Learning_{i,t} + \beta_2 Betweenness\_centrality_{i,t} + \boldsymbol{\theta}\mathbf{C}_{\mathrm{i}} + \boldsymbol{\gamma}\mathbf{Z}_{i,t}$$

$\mathbf{C}_{\mathrm{i}}$ represents a set of time-invariant control variables (such as educational attainment), and $\mathbf{Z}_{i,t}$ represents a vector of time-varying individual- and firm-level control variables (such as tenure, job position characteristics, and firm characteristics, etc.). To test Hypothesis 4 and 5 we include the interactions of *betweenness centrality* and the *contribution/learning* variables in the hazard function.

To control for the possibility of unobserved individual heterogeneity, we also run a linear probability model (LPM) using fixed effects panel data method that directly models the choice of job hopping. The linear probability model with fixed effects is specified as:

$$Prob\left(\mathrm{Job}_{\mathrm{Switch}_{i,t}}\right) = F\left(\beta_0 Contribution_{i,t} + \beta_1 Learning_{i,t} + \beta_2 Betweenness_{centrality_{i,t}} + \boldsymbol{\gamma}\mathbf{Z}_{i,t} + \mu_i + \varepsilon_t\right.$$

Where we assume $F(.)$ is the identity function, and μ_i and ε_{t} represents a set of individual and time period fixed effects. The LPM can be viewed as a linear approximation to the nonlinear model counterpart of $F(.)$ such as binary logistic models.[2]

4. Analyses and Results

[2] As a robustness test, we also run alternative models where the link function $F(.)$ is specified as a logistic function using a population-averaged generalized estimating equations (GEE) approach. We obtained similar results. For brevity, those results are not presented, but are available upon request.

The results of the Cox proportional hazard models are presented in Table 2. In column 1 we presents a baseline model specification where we include only the key variables of interest, *contribution* and *learning*, together with the indicator variable of *SAP employee* as well as the interactions of *SAP_employee* and *contribution/learning* variables. We add a series of individual level control variables, including those related to educational background, tenure, and job title in column 2. In column 3 we present a model that incorporates firm level controls such as industry sector, firm size and firm type, in addition to individual level controls.

[Insert Table 2 about here]

We find support for both Hypothesis 1 ($p < 0.1$) and Hypothesis 2 ($p < 0.05$). Specifically, the estimated coefficient in column 3 suggests that one percent increase in knowledge contribution is associated with 3.8 percent increase in the hazard ratio of a voluntary job hopping. In comparison, learning from the knowledge community has an opposite effect: one percent increase in learning is associated with a 5.1 percent decrease in the hazard ratio of a voluntary job change, consistent with the interpretation that these learning activities represent organizational-specific investments and therefore strengthen the relationship between the individuals and their current employers.

We explore the role of social capital by incorporating the *betweenness centrality* measure together with its interaction with *SAP_employee* indicator. The results are presented in Column 4. The analysis does not lend support to our Hypothesis 3: we do not find a significant positive association between social capital and the likelihood of job hopping. This may be due to the fact that all social ties between the member connected by the forum conversations are homogeneously weak, or due to the sparse (or low density) network that characterize our network data. The result highlights the importance of differentiating between the types of network ties in studying the effect of structural social capital on career development.

To test the moderating effect of social capital, we add the two interaction terms: *contribution*betweenness centrality* and *learning*betweenness centrality* into the regression and present the results in Column 5. Consistent with Hypothesis 4 ($p < 0.1$), we find that the marginal effect of knowledge contribution on job hopping is lower when an individual has accumulated a higher level of social capital. Calculation based on the estimated coefficients suggests that when the level of social capital is low (where betweenness centrality is at 5% percentile, or equal to 0), one percent increase in knowledge contribution is associated with 4.02 percent increase in the hazard ratio of job hopping. In contrast, when the level of social capital is high (where betweenness centrality is at 95% percentile, or equal to .000764), the same amount of increase in knowledge contribution is associated with only 3.01 percent increase in the hazard ratio of job hopping. We also find support for Hypothesis 5 ($p < 0.01$) that the negative effect of learning on job switch is amplified when an individual has greater social capital. Similar calculation based on the results of column 5 suggests that when the level of social capital is low (at 5% percentile of sample), one percent increase in knowledge learning is associated with 3.98 percent decrease in the hazard ratio of job hopping. However, the same amount of increase in learning results in a 5.57 percent decrease in hazard ratio when the level of social capital is high (at 95% percentile of sample).

In Table 3 we present the results of the fixed effects linear probability models. Results of these models have a more intuitive interpretation based on standard marginal effects on probabilities, rather than the marginal effect on hazard ratios as in the previous analyses. Similar to the hazard models, we find support for Hypotheses H1, H2, H4, and H5, but not H3.

[Insert Table 3 about here]

5. Conclusion and Discussion

Internet-enabled communities of practice are rapidly growing and are becoming an effective avenue where professionals can turn to for knowledge exchange and innovation beyond the boundary of their organizations. They are double-edged swords for organizations that embrace them. On one hand, the open channels of communication and interactions in these communities can generate tremendous value and opportunities for organizations (Huang et al. 2012). On the other hand, such knowledge sharing practices could have serious organizational implications including potential talent loss and knowledge spillover to competitors. In this paper, we study if participation in open Internet-enabled communities of practice influences the career development of IT professionals. We found that individuals who contribute a high level of knowledge to the communities are more likely to switch to jobs at other firms. On the other hand, individuals who are primarily knowledge seekers in the communities are more likely to stay with the current employer. Additionally, our data show that social capital accumulated through interactions in the open knowledge community network does not have a direct impact on job hopping; however, it moderates both the effects of knowledge contribution and learning on job hopping.

From a theoretic perspective, this research contributes to the broad literature on communities of practice (Wasko and Faraj 2005), open source communities (Singh et al. 2011) and mass collaboration networks (Zhang and Wang 2012) where a collective individuals work together to achieve certain objectives (e.g., innovation, new ideas, problem solving). For example, earlier studies have focused on identification of factors that motivate individuals to contribute to these communities (Kankanhalli et al. 2005, Roberts et al. 2006). In addition to the intrinsic motivation factors that have been theorized in the literature, researchers have argued for the tangible benefits that members can derive by participating in these communities (Lakhani and von Hippel 2003, Lerner and Tirole 2002). This study is among the first to empirically establish the link between participation in open communities of practice and the realization of long-term career benefits. In addition, while prior literature primarily focuses on the contribution behavior (Wasko and Faraj 2005, Zhang and Wang 2012), our study reveals that various types of participation activities – such as contribution, learning, and network building - are associated with different career benefits such as switching to a more rewarding job or better recognized by the current employer, highlighting the importance of using rich dataset to gain a holistic understanding of individuals' participation in these communities.

This study also adds value to organizational research on voluntary employee turnover, particularly for IT professionals (Jason Bennett et al. 2002, Joseph et al. 2007). While most of these studies examine factors related to internal work environment or external market conditions as predictors for employee turnover, they have so far ignored the employees' activities outside the boundary of the employer organization, such as their participation in Internet-enabled knowledge networks. We show that such activities may indeed influence the loyalty to the current employee and the access to outside job opportunities, and therefore may impose significant cost on employers, such as unintended knowledge spillovers or the loss of human capital and social capital (Jason et al. 2005), highlighting the challenges of retaining talents in today's hyper-connected business environment enabled by information and communication technologies.

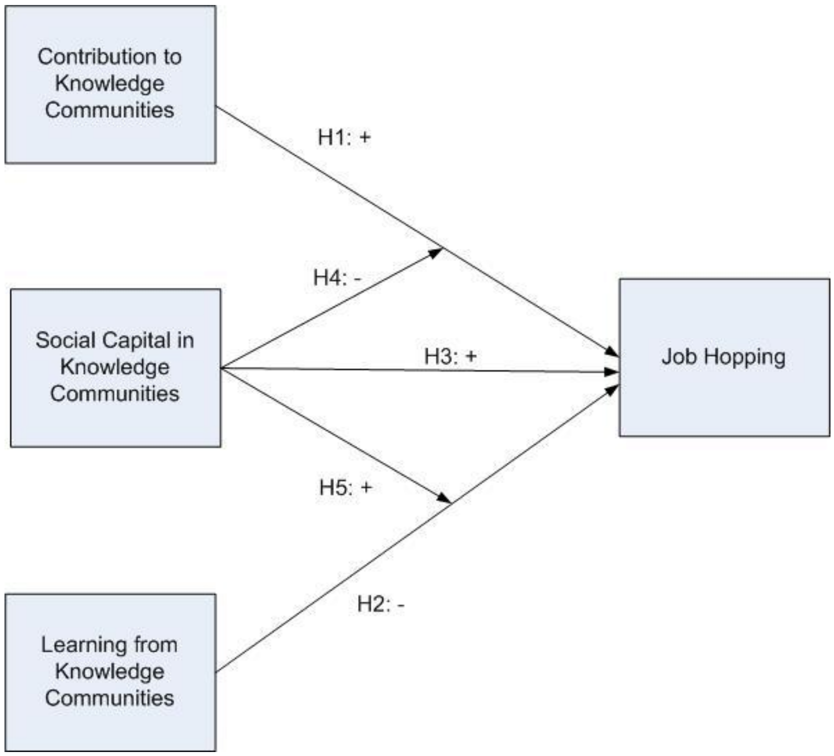

Figure 1: Research Model

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Job switch	6,470	0.215456	0.41117	0	1
Tenure in current company	6,470	4.103246	4.139532	0	35
Tenure in current position	6,470	3.75255	3.854095	0	35
SAP employee	6,470	0.077743	0.267788	0	1
College degree	6,470	0.850541	0.356568	0	1
Master degree	6,470	0.279598	0.448837	0	1
Doctor degree	6,470	0.010201	0.100491	0	1
Cumulative contribution	6,470	24.27295	160.3699	0	3,362
Cumulative learning	6,470	12.75023	137.6141	0	5,400
Betweenness centrality	6,470	0.000253	0.00185	0	0.05697
Management	6,470	0.280835	0.449442	0	1
Non-IT function	6,470	0.028439	0.166236	0	1

Table 2: Hazard Models

VARIABLES	(1)	(2)	(3)	(4)	(5)
Cumulative contribution	0.052**	0.049**	0.038*	0.037†	0.040
	(0.022)	(0.022)	(0.023)	(0.024)	(0.028)
Cumulative learning	-0.046*	-0.062***	-0.051**	-0.052**	-0.040
	(0.024)	(0.024)	(0.024)	(0.025)	(0.032)
Betweenness centrality				6.807	122.602**
				(24.611)	(49.945)
Contribution * Centrality					-13.179*
					(6.962)
Learning * Centrality					-20.865***
					(8.042)
SAP employee	-0.721***	-0.787***	-0.697***	-0.697***	-0.622***
	(0.167)	(0.165)	(0.188)	(0.189)	(0.195)
SAP employee * Contribution	-0.150*	-0.161**	-0.155**	-0.154*	-0.147
	(0.077)	(0.076)	(0.076)	(0.083)	(0.095)
SAP employee * Learning	0.180	0.217*	0.210*	0.212*	0.217**
	(0.115)	(0.114)	(0.115)	(0.115)	(0.095)
SAP employee * Centrality				-6.186	-349.344
				(38.045)	(222.314)
College degree		0.446***	0.453***	0.454***	0.416***
		(0.090)	(0.091)	(0.091)	(0.106)
Master degree		0.070	0.083	0.083	0.084
		(0.060)	(0.062)	(0.062)	(0.070)
Doctor degree		0.557**	0.530**	0.527**	0.441
		(0.227)	(0.232)	(0.234)	(0.315)
Tenure in current company		-0.210***	-0.200***	-0.200***	-0.181***
		(0.047)	(0.047)	(0.047)	(0.041)
$(\text{Tenure in current company})^2$		0.007***	0.007***	0.007***	0.006***
		(0.002)	(0.002)	(0.002)	(0.001)
Tenure in current position		0.173***	0.168***	0.168***	0.151***
		(0.050)	(0.050)	(0.050)	(0.045)
$(\text{Tenure in current position})^2$		-0.008***	-0.008***	-0.008***	-0.007***
		(0.002)	(0.002)	(0.002)	(0.002)
Management		-0.451***	-0.505***	-0.505***	-0.469***
		(0.067)	(0.069)	(0.069)	(0.072)
Non-IT function		0.058	-0.041	-0.041	-0.022
		(0.161)	(0.167)	(0.167)	(0.195)
Industry Dummies	No	No	Yes	Yes	Yes
Firm size Dummies	No	No	Yes	Yes	Yes
Firm type dummies	No	No	Yes	Yes	Yes
No. of subjects	904	904	904	904	904
Observations	6,470	6,470	6,470	6,470	6,470
No. of failures	1,394	1,394	1,394	1,394	1,394

Notes:
Cox proportional hazard models in all columns. Standard errors in parentheses. Also included in column 5 are 3-way interactions *SAP employee * Contribution * Centrality* and *SAP employee * Learning * Centrality*.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, † $p < 0.15$.

Table 3: Linear Probability Models

VARIABLES	(1)	(2)	(3)	(4)	(5)
Cumulative contribution	0.015**	0.016**	0.012*	0.012*	0.014*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Cumulative learning	-0.018**	-0.021***	-0.020***	-0.019**	-0.019**
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Betweenness centrality				-4.494	25.037**
				(4.690)	(10.601)
Contribution * Centrality					-3.775***
					(1.430)
Learning * Centrality					-3.749***
					(1.409)
SAP employee	-0.189***	-0.184***	-0.106*	-0.109*	-0.109*
	(0.046)	(0.050)	(0.059)	(0.059)	(0.059)
SAP employee * Contribution	-0.021	-0.015	-0.012	-0.005	-0.003
	(0.017)	(0.018)	(0.019)	(0.019)	(0.019)
SAP employee * Learning	0.038	0.034	0.035	0.034	0.030
	(0.026)	(0.028)	(0.028)	(0.028)	(0.029)
SAP employee * Centrality				-10.646**	-14.579
				(4.753)	(17.735)
Tenure in current company		0.024**	0.028***	0.027***	0.027***
		(0.010)	(0.010)	(0.010)	(0.010)
(Tenure in current company)^2		-0.001	-0.001	-0.001	-0.001
		(0.000)	(0.000)	(0.000)	(0.000)
Tenure in current position		0.026***	0.024**	0.025**	0.025**
		(0.010)	(0.010)	(0.010)	(0.010)
(Tenure in current position)^2		-0.001	-0.001	-0.001	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)
Management		-0.087***	-0.081***	-0.082***	-0.082***
		(0.024)	(0.025)	(0.025)	(0.025)
Non-IT function		0.010	0.001	0.001	0.001
		(0.060)	(0.063)	(0.063)	(0.063)
Constant	0.220***	0.077***	0.123	0.123	0.113
	(0.015)	(0.023)	(0.246)	(0.247)	(0.245)
Year dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	Yes	Yes	Yes
Firm size dummies	No	No	Yes	Yes	Yes
Firm type dummies	No	No	Yes	Yes	Yes
Observations	6,470	6,470	6,470	6,470	6,470
Number of subjects	904	904	904	904	904
R-squared (without FE)	0.008	0.043	0.054	0.055	0.056
R-squared (with FE)	0.2303	0.2574	0.2658	0.2668	0.2677

Notes:
Fixed effect panel data models in all columns. Robust standard errors in parentheses. Also included in column 5 are 3-way interactions *SAP employee * Contribution * Centrality* and *SAP employee * Learning * Centrality*.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

References

Adler, P.S., S.-W. Kwon. 2002. Social capital: Prospects for a new concept. *Academy of Management Review*. **27**(1) 17-40.

Alavi, M., D.E. Leidner. 2001. Review: Knowledge management and knowledge management systems: Conceptual foundations and research issues. *MIS Quarterly*. **25**(1) 107-136.

Ardichvili, A., V. Page, T. Wentling. 2003. Motivation and barriers to participation in virtual knowledge-sharing communities of practice. *Journal of Knowledge Management*. **7**(1) 64-77.

Belliveau, M.A., C.A.O.R. Iii, J.B. Wade. 1996. Social capital at the top: Effects of social similarity and status on ceo compensation. *The Academy of Management Journal*. **39**(6) 1568-1593.

Brown, J.S., P. Duguid. 1991. Organizational learning and communities-of-practice: Toward a unified view of working, learning, and innovation. *Organization Science*. **2**(1) 40-57.

Burt, R.S. 1992. *Structural holes: The social structure of competition*. Harvard University Press.

Burt, R.S. 1997. The contingent value of social capital. *Administrative Science Quarterly*. **42**(2) 339-365.

Burt, R.S. 2000. The network structure of social capital. B.M. Staw, R.I. Sutton, eds. *Research in organizational behavior*, Elsevier, 345-423.

Cappelli, P. 2000. A market-driven approach to retaining talent. *Harvard Business Review*. **78**(1) 103-111.

Chan, J., K. Husted. 2010. Dual allegiance and knowledge sharing in open source software firms. *Creativity & Innovation Management*. **19**(3) 314-326.

Cummings, J.N. 2004. Work groups, structural diversity, and knowledge sharing in a global organization. *Management Science*. **50**(3) 352-364.

Fallick, B., C.A. Fleischman, J.B. Rebitzer. 2006. Job-hopping in silicon valley: Some evidence concerning the microfoundations of a high-technology cluster. *The Review of Economics and Statistics*. **88**(3) 472-481.

Freeman, L.C. 1979. Centrality in social networks conceptual clarification. *Social Networks*. **1**(3) 215-239.

Füller, J., G. Jawecki, H. Mühlbacher. 2007. Innovation creation by online basketball communities. *Journal of Business Research*. **60**(1) 60-71.

Gilsing, V., B. Nooteboom, W. Vanhaverbeke, G. Duysters, A. van den Oord. 2008. Network embeddedness and the exploration of novel technologies: Technological distance, betweenness centrality and density. *Research Policy*. **37**(10) 1717-1731.

Gordon, M.E.L.R.T. 1990. Dual allegiance: Renewal, reconsideration, and recantation. *Personnel Psychology*. **43**(1) 37-69.

Granovetter, M.S. 1973. The strength of weak ties. *American Journal of Sociology*. **78**(6) 1360-1380.

Hagedoorn, J., G. Duysters. 2002. Learning in dynamic inter-firm networks: The efficacy of multiple contacts. *Organization Studies*. **23**(4) 525-548.

Huang, P., M. Ceccagnoli, C. Forman, D.J. Wu. 2012. Network of practice, it knowledge spillovers, and productivity: Evidence from enterprise software. *Workshop on Information Systems and Economics (WISE),* Orlando, FL.

Jason Bennett, T., P.S. Lee, J.B. Randall. 2002. Turnover of information technology workers: Examining empirically the influence of attitudes, job characteristics, and external markets. *Journal of Management Information Systems*. **19**(3) 231-261.
Jason, D.S., M.K. Duffy, J.L. Johnson, D.E. Lockhart. 2005. Turnover, social capital losses, and performance. *The Academy of Management Journal*. **48**(4) 594-606.
Joseph, D., K.-Y. Ng, C. Koh, A. Soon. 2007. Turnover of information technology professionals: A narrative review, meta-analytic structural equation modeling, and model development. *MIS Quarterly*. **31**(3) 547-577.
Joskow, P.L. 1987. Contract duration and relationship-specific investments: Empirical evidence from coal markets. *The American Economic Review*. **77**(1) 168-185.
Kankanhalli, A., B.C.Y. Tan, K.-K. Wei. 2005. Contributing knowledge to electronic knowledge repositories: An empirical investigation. *MIS Quarterly*. **29**(1) 113-143.
Lakhani, K.R., E. von Hippel. 2003. How open source software works: “free” user-to-user assistance. *Research Policy*. **32**(6) 923-943.
Lampel, J., A. Bhalla. 2007. The role of status seeking in online communities: Giving the gift of experience. *Journal of Computer-Mediated Communication*. **12**(2) 434-455.
Lee, G.K., R.E. Cole. 2003. From a firm-based to a community-based model of knowledge creation: The case of the linux kernel development. *Organization Science*. **14**(6) 633-649.
Lerner, J., J. Tirole. 2002. Some simple economics of open source. *The Journal of Industrial Economics*. **50**(2) 197-234.
Ma, M., R. Agarwal. 2007. Through a glass darkly: Information technology design, identity verification, and knowledge contribution in online communities. *Information Systems Research*. **18**(1) 42-67.
McPherson, J.M., P.A. Popielarz, S. Drobnic. 1992. Social networks and organizational dynamics. *American Sociological Review*. **57**(2) 153-170.
Millen, D.R., M.A. Fontaine. 2003. Improving individual and organizational performance through communities of practice. *Proceedings of the 2003 International ACM SIGGROUP Conference on Supporting Group Work*, Sanibel Island, Florida, USA.
Mossholder, K.W., R.P. Settoon, S.C. Henagan. 2005. A relational perspective on turnover: Examining structural, attitudinal, and behavioral predictors. *Academy of Management Journal*. **48**(4) 607-618.
O'Mahony, S., F. Ferraro. 2007. The emergence of governance in an open source community. *Academy of Management Journal*. **50**(5) 1079-1106.
Podolny, J.M., J.N. Baron. 1997. Resources and relationships: Social networks and mobility in the workplace. *American Sociological Review*. **62**(5) 673-693.
Porter, L.W., R.M. Steers, R.T. Mowday, P.V. Boulian. 1974. Organizational commitment, job satisfaction, and turnover among psychiatric technicians. *Journal of Applied Psychology*. **59**(5) 603.
Roberts, J.A., I.-H. Hann, S.A. Slaughter. 2006. Understanding the motivations, participation, and performance of open source software developers: A longitudinal study of the apache projects. *Management Science*. **52**(7) 984-999.
Rossi, M.A. 2004. Decoding the free/open source puzzle. A survey of theoretical and empirical contributions, Working paper, Dipartimento Di Economia Politica, Università degli Studi di Siena, Siena, Italy.

Rylander, D., D. Strutton, L.E. Pelton. 1997. Toward a synthesized framework of relational commitment: Implications for marketing channel theory and practice. *Journal of Marketing Theory and Practice*. **5**(2) 58-71.
Seibert, S.E., M.L. Kraimer, R.C. Liden. 2001. A social capital theory of career success. *Academy of Management Journal*. **44**(2) 219-237.
Singh, P.V., Y. Tan, V. Mookerjee. 2011. Network effects: The influence of structural capital on open source project success. *MIS Quarterly*. **35**(4) 813-829.
Tambe, P., L.M. Hitt. 2010. Job hopping, knowledge spillovers, and regional returns to information technology investments. *Management Science*. **forthcoming**.
Wasko, M.M., S. Faraj. 2000. "it is what one does": Why people participate and help others in electronic communities of practice. *The Journal of Strategic Information Systems*. **9**(2–3) 155-173.
Wasko, M.M., S. Faraj. 2005. Why should i share? Examining social capital and knowledge contribution in electronic networks of practice. *MIS Quarterly*. **29**(1) 35-57.
Wenger, E., R. McDermott, S. William. 2002. *Cultivating communities of practice*. Harvard Business School Press, Boston, MA.
Wenger, E.C., W.M. Snyder. 2000. Communities of practice: The organizational frontier. *Harvard Business Review*. **78**(1) 139-145.
Wilson, J. 2009. Social networking: The business case. *Engineering and Technology*. **4**(10) 54-56.
Zhang, X., C. Wang. 2012. Network positions and contributions to online public goods: The case of chinese wikipedia. *Journal of Management Information Systems*. **29**(2) 11-40.